The Marketer’s Cookbook: Recipes for Using Predictive Analytics

CRM Evolution
2017
Meet our consumers

- Julie and Sam
- Amy
- Cathy and Bryan
Data-driven segments

1. Married people who do not have our credit card

2. Single people who do not have our credit card, and who have paid greater than 20% of their mortgage loan

3. People who have $2,000 or less on our credit card, who also come to the branch (rather than banking online)
Finding the patterns

Married people who do not have our credit card

Single people who do not have our credit card and who have paid greater than 20% of their loan

People who have $2000 or less on our credit card, who also come to the branch (rather than banking primarily online)
Campaign results: acting on the insights

• A campaign manager might select likelihood values from 80 to 100, thus taking the **top 20% of prospects** for the campaign.

• Or a campaign manager **might target by segment**.

Married people who do not have our credit card
For example, targeted campaigns for each segment (or even for each person)

- Custom campaigns using the segment information are created and sent.

- Cross-sell modeling typically performs at least twice as good as mailing without using any targeting.
Agenda

• What do we mean by Predictive Analytics?
• Analytics made simple
  ◦ Data sources and data prep
  ◦ Modeling
    – Process
    – Selecting algorithms
    – Model building
  ◦ Analysis and interpretation
• More ways predictive analytics shapes relationships
• Future perspective: AI
• Key takeaways
What is predictive analytics?

Predictive Analytics helps connect **data** to **effective action** by drawing reliable conclusions about current conditions and **future** events.

*Gareth Herschel, Research Director, Gartner Group*

Enabling businesses to use **predictive models** to exploit patterns found in historical data to **identify** potential **risks** and **opportunities** before they occur.
# Predictive analytics: questions you can address

<table>
<thead>
<tr>
<th>Strategic Questions</th>
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<tr>
<td><strong>Sales &amp; Marketing</strong></td>
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<tr>
<td>• What campaigns and offers have the highest chance of success and what types of customers should we be targeting?</td>
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<td>• What products sell well together and what products are consumers most likely to purchase?</td>
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<td>• Which CRM activities are more effective in leading to higher sales opportunities?</td>
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<td><strong>Finance</strong></td>
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<td>• How can we lower marketing costs without sacrificing effectiveness or hampering sales?</td>
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<td>• How accurate and reliable is our current forecast (and targets) based on historical trends?</td>
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<td><strong>Operations</strong></td>
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<td>• What defects occur in our credit card fulfillment process and can we prevent the most frequent issues?</td>
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<td>• Can we forecast our call center staffing levels based on the expected response from marketing campaigns?</td>
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Big Data makes it personal

• As the data gets bigger, it contains a higher volume of more specific customer interactions
  ◦ Mass advertising
  ◦ Segmented marketing
  ◦ Personalized contact
  ◦ Individually targeted and custom messaged
Predictive Analytics can use ALL available data

**Interaction data**
- Email / chat transcripts
- Call center notes
- Web click-streams
- In person dialogue

**Descriptive data**
- Attributes
- Characteristics
- Self-declared info
- (Geo)demographics

**Behavioral data**
- Orders
- Transactions
- Payment history
- Usage history

**Attitudinal data**
- Opinions
- Preferences
- Needs & desires
- Survey results
- Social media

360-degree View of Problem
Building a predictive model

• Goal: which “customers” would be likely to accept an offer for a Home Equity Line of Credit (HELOC)

  “Customers” are people who have a mortgage with our bank.

• We used algorithms to look for patterns in the data.

• This process shows how a model uses data about customers who responded to a similar offer in the past.

• The model is “predictive” in the sense that we can pick out which new (or future) customers are more likely to respond favorably to the new offer.

*This data is representative. Your data and findings will be different and more detailed.
3 steps to building a predictive model

This diagram shows **the 3 key phases of the modeling process**, including:

1. Data coming in and being prepared.
2. A model being created and evaluated.
3. And finally, deployment of the ranked customers into the campaign table of the database.
Step 1: Data preparation

Staging and prep of the data can represent 50-70% of the total effort.

Example of data prep:
Age is calculated, and then the input variables (year, month, day) are removed to minimize risk of using Personally Identifiable Information (PII).
Personally identifiable information is often present in data tables.

As it’s not necessary for most analyses, it should be removed as early as possible - often prior to the time an analyst sees the data.
To test how well our model predicts real behavior, we divide or “partition” the data.

About 50% of the data has been assigned to use in model building.

The other half is reserved for model validation testing.
Step 2: Modeling

- Based on our historical data: 38% of customers currently accept the offer.

- The algorithm we create will discover significant patterns that make up:
  - The 38% who accept the offer.
  - The 62% who do not accept it.

This demonstration uses a decision tree to build a set of rules that describe the key patterns discovered in the data.
The algorithm is predicting the Target (Who will Accept Offer 1)
- using patterns discovered from combinations of the Predictors (our other input variables)
Finding the patterns
Married people who do not have our credit card

Single people who do not have our credit card and who have paid greater than 20% of their loan

People who have $2000 or less on our credit card, who also come to the branch (rather than banking primarily online)
Interpretation: Is the model any good?

- Overall, the model was equally accurate in the Modeling and Validation datasets (73.66% is almost the same as 73.76%)
- Specifically, the model accurately identified 542 acceptors and 1083 rejecters in the Modeling dataset
Understanding the model with a gains curve

In the perfect model, we **contact 38% of the people** and our targeting is so good, we reach **100% of those who are going to accept the offer**.

The **horizontal axis** shows **100% of people in the dataset**. These people are sorted in descending order of confidence in accepting the offer.

The **vertical axis** shows **100% of the people who accepted the offer**.

The **diagonal line** shows a uniform random distribution of responses.

In other words, if 10% of the people had 10% of the acceptances, and if 20% of the people had 20% of the acceptances, we would get the diagonal line.
Our model is not the perfect one, but we do perform much better than without a model. **Green** curve is above the diagonal line.

By mailing to 40% of the list, we’ll hit 65-70% of the people who will accept the offer.

The **upper left red line** shows the perfect model. If all of the most confident results are correct, we will get to 100% of the vertical axis at about 38% of the file, because 38% of the people accepted the offer.

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Decision trees are just one family of algorithms

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<tr>
<th>Use?</th>
<th>Model type</th>
<th>Model parameters</th>
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IBM case study

What if predictive analytics could bring science to Optimizing scarce marketing resources?

Leveraging predictive analytics, First Tennessee Bank combined a granular understanding of the needs of customer segments with real P&L data to optimize its marketing spend, focusing on programs that deliver the highest ROI.

First Tennessee’s model relies on constantly updated customer account information, enabling it to detect changes in service consumption patterns and preferences.

“Our aim was to shift from the ‘marketing-as-an expense’ mindset to the idea that marketing is a true profit driver.” — Dan Marks
Chief Marketing Officer

Real Business Results

- 600% overall return on its investment through more efficiently allocated marketing resources
- 3.1% increase in marketing response rate through more accurate targeting of offers to high-value customer segments
- 20% reduction in mailing costs and 17% reduction in printing costs due to the ability to target the most attractive segment for specific offers
Use cases
Churn Analysis - Customer Retention

- **Problem**: Customers are leaving
- **Resolution**: Predict which ones are most likely to leave and why. Prepare targeted retention messages and incentives, so the call center is ready when customers call.
- **Process**:
  - Using historical data, build models predicting which customers are most likely to leave and why
  - Predict risk level and reasons for each customer and store in database, along with prepared response text
Customer acquisition

- **Problem**: We need more customers
- **Resolution**: Send promotions to those most likely to accept our offer
- **Process**:
  - Obtain data showing who accepted similar offer in the past
  - Purchase demographic data about people
  - Build models that match buyers and demographics
  - Use the models to rank the prospects
Cross-sell and up-sell

**Problem:** Let’s make the customers we have more profitable by selling them more stuff or stuff with a higher margin

**Resolution:** Predict which ones are most likely to buy and why. Present targeted offers to those most likely to buy.

**Process:**
- Build predictive models from historical data.
- Use the models to understand reasons for purchases.
- Predict buying propensity and reason for each customer.
Next best offer

- **Problem**: If a customer rejects my first offer, I’d like to make a second offer that I think they will accept.

- **Resolution**: Pre-load the data warehouse with the best offer and the next best offer for each customer.

- **Process**:
  - Using historical data, build models that predict the likelihood of each customer to accept each offer.
  - Rank the offers and align this information with the call center.
  - Use special models that adjust propensity based on prior choices.
Customer profitability segmentation

• **Problem**: Not sure which customers are most important.
• **Resolution**: Find the most profitable customers and what make them this way. Work to keep these, and to bring more people into the high profitability group
• **Process**:
  ◦ Decile the customers on profitability
  ◦ Profile / Describe the customers in each group
  ◦ Model the customers based on profitability to discover optimal segments
**Problem**: We have so many different products, customers may not know which one to chose. Some choices are more beneficial to our business than others.

**Resolution**: Give customers a ranked list of choices

**Process**:
- Create models to classify each person’s likelihood to purchase each item
- Provide the customer with a ranked list of choices
What technologies are required?

Tools to manage the process:

• **Collecting the data** *(Excel, data warehouse, APIs, frontline data entry)*

• **Integrating the data sources** *(data warehouse)*

• **Analytics workbench to generate actionable insights** *(predictive analytics, statistical analysis)*

• **Reporting** *(data visualization and dashboarding tools)*

• **Archiving** *(data warehouse, cloud storage)*
Future perspective: AI
Analytics make marketing more effective

• **Prioritize** – Rank likelihood, rank $ value

• **Describe** – Make segments

• **Evaluate** – Test everything for success in the field

• **Monitor** – Watch for changes over time

• **Choose the best, get rid of the rest** – Make decisions based on the analytics

• **Iterate** – gather more data and improve over time
Key takeaways

1. Data Mining algorithms are incredibly smart data-wise, but often dumb business-wise.

2. Algorithms find patterns in data, but we’re looking for patterns in business behavior.

3. Only significant and actionable business patterns are interesting - computers can’t always decide that.

4. Engaging people with business understanding and data understanding is so important.

5. The software will run on a laptop, and your data files can be in Excel.
A little about us

Strategy | Analytics | Insights | Action
---|---|---|---

### Highlights and credentials

- Recognized by Forrester Research for our work in culture change, analytics, and CX transformation
- Featured speaker on predictive analytics in banking, Financial Brand Forum 2017
- Featured speaker on analytics best practices, Predictive Analytics World ‘17
- Featured speaker, BAI Retail Delivery Annual Conference 2012-2016
- Faculty Fellow, Pacific Coast Banking School, August 2012
- Featured speaker on social media data mining, American Bankers Association 2013

### Recent press

- The Financial Brand, 2017
- Fortune, June 2014
- Fox Business, January 2014
- Loyalty Magazine, Summer 2012
- Destination CRM, May 2012
- American Banker/Bank Technology News, Jan 2012
- BAI - Retail Banking Strategies, Jan 2012
- ABA Banking Journal, Jan 2012
- Social Business Today, Customer Experience Management @ TMC.net, and other blogs and online publications
Thank you

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